# Deep Learning Model for Demolition Waste Prediction in a Circular Economy

**Abstract**

An essential requirement for a successful circular economy is the continuous use of materials. Planning for building materials reuse at the end-of-life of buildings is usually a difficult task because limited time are usually made available for building removal and materials recovery. In this study, deep learning models were developed for predicting the amount (in tons) of salvage and waste materials that are obtainable from buildings at the end-of-life prior to demolition. Datasets used for deep neural network model developments were extracted from 2,280 building demolition records obtained from the practitioners in the UK Demolition Industry. The data was partitioned into training, testing and validation datasets in the ratio 8:1:1. Deep learning models were developed with a deep learning framework in R programming environment. The average R-squared value for the three deep learning models is 0.97 with Mean Absolute Error between 17.93 and 19.04. The models were evaluated with four scenarios of a case study building design. The results of the evaluation show that, given basic features of buildings, it is possible to predict with a high level of accuracy, the amount of materials that would be recovered from a building after demolition. The models developed will provide decision support functionalities to demolition engineers and waste management planners during the pre-demolition audit exercise.

***Keywords:*** *Deep learning, Deep Neural Network, Buildings' End-of-Life, Circular Economy, Building Materials*

## 1 Introduction

Enabling sustainable consumption and environmental sustainability require concerted efforts among the stakeholders in a circular economy (CE). Although there is increasing awareness towards sustainable consumption and development (Fuchs et al., 2016), there is the need for systems and solutions that efficiently support processes and operations that lead to sustainability, especially in the architecture, engineering and construction (AEC) industry (Cheng and Ma, 2013). Determining the maximum derivable economic and environmental values from a building at the end-of-life prior to deconstruction and demolition is one of the key requirements for sustainability in the construction and demolition (C&D) industry (Song et al., 2017). Pre-demolition audits have been identified as a tool that provides valuable information required by stakeholders (clients, architects, engineers, contractors, planners etc.) in the C&D industry to optimise existing buildings as part of decommissioning, deconstruction and demolition process (Hurley, 2003). In the UK, pre-demolition audits are part of the requirements within the Building Research Establishment Environmental Assessment Method (BREEAM) construction scheme which specifies that the audit should ascertain if materials recovery for reuse is feasible and maximise materials recovery from the demolition for subsequent up-cycling (Adams, 2013).

Through various legislations and the adoption of the circular economy model, concerted efforts are being put in place by governments of nations to extend the lifespan of building materials in the economy to conserve the embodied energy of materials (COM, 2014). To facilitate adequate planning for materials recovery and reuse at the end-of-life, it is essential to have access to information about the material type and quantities that would be generated from the process. This information is presently being obtained through pre-demolition audits in Europe (European Commission, 2018). Undertaking a pre-demolition audit could be very challenging, especially where little or no information is available. In circumstances where blueprints and sectional drawings that can be used to interpret the construction methods and materials used in the building are available, generating pre-demolition audits could be completed as a desktop study and complemented by visits to confirm the blueprints (Hurley, 2003). Completing pre-demolition audit as a desktop study is impracticable as most buildings that are due for demolition do not possess necessary 2D and 3D information. The required information about buildings for pre-demolition audits generation is usually gathered through direct measurement and examination of the building during site visits. This process of generating pre-demolition audit is very tedious, cumbersome and time-consuming (Hurley, 2003). It is also difficult to adequately prepare for how the arisings from demolition activities are reused, recycled or landfilled. This bottleneck usually leads to unexpected costs in arising separation, transportation and processing. This study provides an intelligent and objective approach for estimating the nature and volume of arisings and corresponding use cases (i.e. reusable, recyclable and items to be disposed) from basic building properties as input.

Limited time is usually made available for old building removal from sites before the construction of new one commences. The demolition engineers have no luxury of time to allow for a thorough pre-demolition audit exercise. (Rose, 2019). The successful application of deep learning in different areas, for example, (Ajayi et al., 2019; Wan et al., 2014), informed our belief that its application for predicting demolition wastes will facilitate timely access to information about potential waste arisings from buildings at the end-of-life thereby supporting efficient planning for materials reuse and recycling. The novelty of this work is in the application of a carefully selected machine learning model to address the challenges of estimating end-of-life values of buildings.

This study employs the deep learning technique to develop a computational tool for predicting the amount of building materials that are obtainable from building demolition exercise. This is to facilitate timely access to end-of-life properties of buildings to support decision making in terms of skip requirement planning, waste transfer station and direct reuse identification. The specific objectives are:

i. to design deep learning models for predicting amount in tons of building materials that would be generated from building after demolition.

ii. to assess the accuracies of the models with the test dataset.

iii. to evaluate the models with a case study building design.

The rest of the paper is organised as follows: The literature review is covered in section 2, where approaches to predicting and estimating C&D waste and their limitations are presented. Various applications of deep learning models are also presented in section 2. The theoretical underpinning of this study is presented in section 3. Section 4 contains the methodology adopted for this study, where data description and model development are demonstrated. Model testing and evaluation are also presented in section 4. The Discussion and Conclusion are presented in sections 5 and 6.

## 2 Literature Review

In this section, various approaches for estimating construction wastes and demolition arisings are presented. Limitations of the existing methods are also discussed. Further, the application of deep learning models in diverse areas such as speech recognition, image processing, energy prediction etc. are presented.

### 2.1 Approaches to construction and demolition waste estimation in a CE

According to Wu et al., (2014), existing construction and demolition waste estimation and quantification process can be grouped into three categories, namely: construction waste, renovation waste and demolition waste. The result from the estimation and quantification of C&D waste process could provide necessary information to stakeholders to assess the potential wastes quantities, allowing for adequate preparation for their sustainable management (Yuan and Shen, 2011). The current method of estimating pre-demolition audit (also called waste

98 audit) is largely manual and requires a lot of time and effort since information such as material volume needed to be measured or retrieved from available documents manually. Previous works that have tried to estimate C&D wastes are presented in table 1. These works consider the various group of waste such as C&D waste, construction waste only and demolition and refurbishment waste at different coverage level (i.e. project level or regional level).

Table 1: C&D Waste Prediction and Estimation Methods

| *SN* | **Method of Prediction/ Estimation and Sources** | **Group of Waste** | **Coverage Level** | **Comment** |
|---|---|---|---|---|
| *1* | BIM based model for waste estimation<br><br>Cheng & Ma (2013) | Demolition and renovation | Project | This tool leverages the functionalities provided by BIM to estimate the demolition waste. It requires a, properly developed BIM model of building to function. BIM models are not available for most of the buildings that are due for demolition. |
| *2* | Hybrid model based on gray model and support vector regression<br>Song, Wang, Liu, & Zhang, (2017) | C&D | Region | This approach to C&D waste prediction is based on the annual waste output of a region. It will be difficult if not impracticable to apply the approach at an individual project level. |
| *3* | Li, Zhang, Ding, & Feng, (2016)<br>Quantitative models for waste estimation based on material quantity takeoff, conversion ratios between different waste measurement units and work breakdown structure. | Construction only | Project | The quantitative models developed used work breakdown structure (WBS), material quantity takeoff, etc. for predicting construction waste. These models rely on the availability of materials quantity takeoff for their operation. The quantity-takeoff information is usually not available for most old buildings. |

Cheng & Ma (2013) developed a tool for estimating demolition and renovation waste in Hong Kong, based on the functionalities provided by the Building Information Modelling

(BIM). The BIM based tool developed is capable of estimating demolition wastes from a properly prepared 3-D model of buildings. Akanbi et al., (2018) developed a BIM-based system for estimating salvage value of building materials through a building's lifecycle. In our opinion, these BIM based systems are excellent tools to support the demolition and refurbishment waste estimation of buildings with BIM models. The usability of the models is limited because almost all the buildings that are due for demolition and refurbishment has no BIM model. In fact, in some cases, the 2-D drawings are non-existent, limiting the usability of the tool.

A hybrid model based on the model (GM) and support vector regression (SVR) for predicting annual C&D waste in China was developed in (Song et al., 2017). A transition matrix was used to compute the C&D waste quantities after the annual total area of construction (ATAC) has been estimated. This approach to C&D waste prediction is based on the annual waste output of a region. It will be difficult if not impracticable to apply the approach at an individual project level. Quantitative models for construction waste estimation were developed in (Li et al., 2016) in which material quantity takeoff, conversion ratios between different waste measurement units, wastage levels of different materials used in different work packages and work breakdown structure (WBS) are integrated. These tools rely on the availability of materials quantity takeoff for their operation. The materials quantity-takeoff information is usually not available for most old buildings. Also, the models only estimate construction waste.

In summary, while the current state-of-the-art approaches for estimating the C&D wastes provide a huge improvement over the manual method of estimating the wastes through pre-demolition audits, the challenges with them include their inability to be usable for old building stocks. For example, the approach developed in (Cheng and Ma, 2013) can only be used with buildings with properly prepared 3D model. The hybrid model developed in (Song et al., 2017) can only be used to estimate annual C&D waste output of regions. This work seeks to fill this gap by developing machine learning models to estimate the materials output from buildings based on the basic features of the building.

## 2.2 Deep Learning Models and Application

Deep learning (DL) is a computational technique that utilises multiple hidden processing layers for learning data representations and relationship with multiple levels of abstraction (LeCun et al., 2015). Deep learning models are neural networks that are made up of three principal layers, i.e. input, hidden and output layers. The hidden layers contain several layers with a large number of neurons in each layer. Different deep learning architectures have been used in different domain with a high level of performance reported. For example, unsupervised, pre-trained or feedforward neural networks which include Deep Belief Network (Lee, Grosse, Ranganath, & Ng, 2011), Deep Neural Network (Fayek et al., 2017), Recurrent Neural Networks (Schmidhuber, 2015), and Convolutional Neural Networks (Sharif Razavian et al., 2014) are examples of common deep learning architecture. In feedforward deep neural networks, data flows from the input layer to the output layer without looping back. Recurrent neural networks, allow data to flow in any direction and have been used extensively in language modelling (Sutskever et al., 2014). Convolutional Neural Networks are standard for computer vision applications (Klein et al., 2017). A summary of the description of these deep learning architectures is presented in table 2. In the present work, the feedforward architecture has been employed because of its simplicity and suitability for regression problems.

Table 2: Deep Learning Architecture and Model Description

| DL Model | Description |
|---|---|
| **Deep Neural Network** | Deep Neural Networks (DNN) are feed-forward neural networks that comprise multiple layers of transformations and nonlinearity with the output of each layer feeding the subsequent layer (Fayek et al., 2017). Detail description of DNN is provided in the section 3.3. |
| **Convolutional Neural Network** | Convolutional Neural Networks (CNN) are the architecture of deep learning suitable for image processing. According to (LeCun et al., 2015), CNNs are designed to process data in the form of multiple arrays, e.g. signals and sequences, images or audio spectrograms and video or volumetric images. |
| **Recurrent Neural Network** | Recurrent Neural Network (RNN) processes an input sequence one element at a time, maintaining in their hidden units, a state vector that implicitly contains information about the history of all the past elements of the sequence (LeCun et al., 2015). RNNs are parameterized families of probability distributions that extrapolate a finite training set to a distribution over an entire space (Sutskever, 2013). |
| **Deep Belief Network** | This is are probabilistic generative models that contain multiple layers of stochastic, latent variables (Heaton, 2015). Deep Belief Network is a stack of Restricted Boltzmann Machines with a single layer of feature-detecting units. (Schmidhuber, 2015) |

Our motivation for employing deep learning in this study is because of its capacity to discover complex structures and relationships in high-dimensional data and its ability to dynamically construct new task-specific attributes from data representations (Wan et al., 2014). This feature has enabled DL models to surpass existing machine learning approaches, as demonstrated in various classification and regression works (Mayr et al., 2016). For example, deep learning has been successfully used in domains such as vision and image processing (Pang et al., 2017), speech recognition (Fayek et al., 2017), and traffic control (Zhao et al., 2017). Other application areas are power and energy consumption (Fan et al., 2017), credit scoring (Luo et al., 2017), drug molecule analyses (Ma et al., 2015), building cooling load prediction (Fan et al., 2017; Luo et al., 2019), natural language processing (Costa-jussà et al., 2017), and medicine (AlRahhal et al., 2016). Other important features of DL models are the ability to work better with massive data sets and handle high dimensional, nonlinear relationships in a sparse, noisy data (Mamoshina et al., 2016). DL models also possess the capability to track and generate attribute importance and contribution towards the achievement of a training goal (Lee et al., 2017). Details of the mathematical description of deep neural networks are presented in section 3.3.

# 3 Theoretical Background to the Study

Taking a cue from Akinade, (2017), this study is underpinned by two well establish theories, as shown in figure 1. These theories are (i) theory of artificial intelligence and (ii) theory of the tragedy of the commons. The two theories are obtained from the fields of machine intelligence and resource management. Details of these theories are presented in the following subsections.

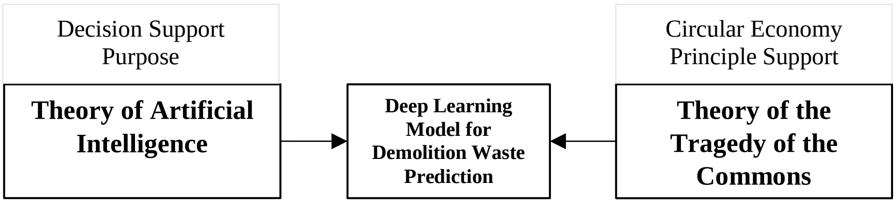


Figure 1: Theoretical Underpinning of this Study

## 3.1 Theory of the tragedy of the commons

The theory of the tragedy of the commons explains the danger inherent in the selfish indiscriminate use of a finite resource (Hardin, 1968). A wide range of common resources was enunciated by (Hardin, 1968) and sought to incorporate various restraints to encourage a balanced coexistence within the society. The theory of the tragedy of the commons can be considered as providing the basis for the principle of material circularity in a circular economy. Considering construction materials and landfill sites as a common resource which are finite in nature, then this work leverages the development in AI to facilitate planning for material reuse and recycling as well as the reduction in the amount of materials that are landfilled.

## 3.2 Theory of the artificial intelligence

This study is hinged on the proposition at the Dartmouth conference of 1956 on artificial intelligence(AI) that "every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" (McCarthy et al., 2006)., Although the philosophical issue of whether a machine could act intelligently is a topic that generates ongoing discussion (Akinade, 2017), the epistemological and heuristic part of AI form the theoretical basis for this study. While the epistemological part of AI is concerned with the nature of information about the world, the heuristic part deals with mechanisms of using the information stored in the memory of machines for solving and interpreting solutions to problems. The epistemological and heuristic suitability is required to define the existing pre-demolition audit estimation problem with a computational tool.

## 3.3 Mathematical Description

The solution developed in this study is represented symbolically to show the relationship between the input features and the resultant output as would be represented in the memory of a computer machine. Basic features of building that include (i) gross floor area (GFA), (ii) building volume (iii) number of floor (iv) building architype and (iv) building usage type, are the independent variable (*X)* and the amount in tons of building material is the dependent variable (*Y*). The goal is to develop a relationship between the basic building features and the materials outputs that are expected from the building demolition. Equation (1) shows the description of the relationship between the basic building features and the amount of the recyclable material. The actual relationship between the building features and the recyclable amount are established during the training of the DNN model based on the internal state of the machine.

$$Recyclable = f(gfa, volume, floors, usage, architype) \quad (1)$$

Similarly, equations (2) and (3) show the description of the relationship between the basic building features and reusable and landfill amounts.

$$Reuse = f(gfa, volume, floors, usage, architype) \tag{2}$$

$$Landfill = f(gfa, volume, floors, usage, architype) \tag{3}$$

The underlying principle in this work is to use the basic feature of a building to predict the amount of the building materials and their categories (reusable, recyclable and landfill) that will result from building deconstruction and demolition at the end-of-life.

Through training, the computer machine (DNN machine in this case) learn the relationship between the dependent variable and independent variables and maps an input to the output, i.e. $Y = f(X)$. This mapping is parameterised by weights, which are optimised during the learning process. The machine uses data samples to train a model to make predictions while passing learned features of data through different layers of abstraction. DNNs usually have many hidden layers with large neurons, and thousands of neurons may exist in each layer (Ciresan et al., 2012). This feature distinguishes DNNs from the traditional artificial neural networks that have a modest number of neurons. The deep learning process is formally described as follows. Let the output of a neuron at layer $\ell$ be denoted by $h^{\ell}$, and its input vector coming from the previous layer by $h^{\ell-1}$, then we have the activation of neurons in matrix notation defined as $h^{\ell} = \sigma\left(b^{\ell}+W^{\ell}h^{\ell-1}\right)$. $h^{\ell}$ denotes the output of a neuron at layer $\ell$, and its input vector by $h^{\ell-1}$ coming from the previous layer, $b^{\ell}$ is a vector of biases, $W^{\ell}$ is a matrix of weights and $\sigma(\cdot)$ is the activation function, which is applied element-wise. Activation functions are nonlinear transformations of weighted data. Examples are tanh, rectified linear unit, sigmoidal and maxout.

At the input layer, the input vector, $x = h^o$, is the raw data to be analysed by the network. The output vector $h^\ell$in the output layer is used to make predictions. For a multi-class classification task, the output of layer $\ell$ is defined as in equation (4).

$$h_i^\ell = \frac{exp\left(b_i^\ell + W_i^\ell h^{\ell-1}\right)}{\sum_j exp\left(b_j^\ell + W_j^\ell h^{\ell-1}\right)} \qquad (4)$$

where $W^\ell$ is the matrix of weights, $W_i^\ell$ is the $i^{th}$ row of $W^\ell$, $h_i^\ell > 0$, and $\sum_i h_i^\ell = 1$ and for a regression task, the output is given in equation (5) as

$$h_i^\ell = \alpha_{ok} + \alpha_k \sigma\left(b_i^\ell + W_i^\ell h^{\ell-1}\right) \qquad (5)$$

where $\alpha_{0k}$ represents the bias applied to the output layer and $\alpha_k$ the set of weights between the previous layers and the last. The outputs and the target function y are used together in a cost function $\mathcal{E}\left(h^\ell, \mathcal{Y}\right)$, which is convex in $b^\ell + W^\ell h^{\ell-1}$. The cost functions for both classification and regression tasks are defined in equations (6) and (7).

$$\mathcal{E}\left(h^\ell, y\right) = -log h_y^\ell, \qquad Classification \qquad (6)$$

$$\mathcal{E}\left(h^\ell, y\right) = \left\|y - h_y^\ell\right\|^2, \qquad Regression \qquad (7)$$

$h_y^\ell$ is the network output and y is the desired response. The architecture of a typical feedforward deep neural network is presented figure 2. The input layer provides the required dataset for the model to learn the patterns and map them to the corresponding output.

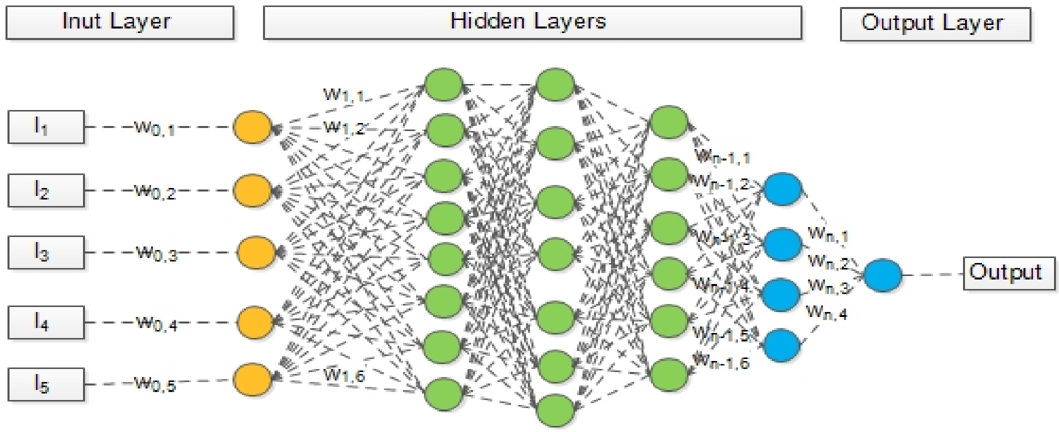


Figure 2: Architecture of Feedforward Deep Neural Network

## 4 Research Methods

The process of data acquisition, data pre-processing, feature selection and deep learning model development are presented in this section. The quantity and end-of-life use case of building materials are predicted by using DL based models. The data acquisition and pre-processing, as well as model development, are presented in the following subsections. The general research outline for this study is presented in figure 3. Data pre-processing and selection of variables are carried out to clean the deconstruction and demolition datasets obtained from the UK members of Institution of Demolition Engineers (IDE) and National Federation of Demolition Contractors (NFDC). Three DNN models were constructed to set relationships between dependent and independent variables. Selected variables from the dataset make up the independent variables, while recyclable, reusable and landfill components of the total recoverable building materials make up the dependent variables. Relevant optimisation techniques are then used to maximise each model's prediction accuracy. The DNN model interpretation is presented next. The Interpretable Machine Learning (IML) features of R-package are used to present the interpretation of the models. Lastly, the prediction accuracies of the models are evaluated on test data using evaluation metrics that include Mean Absolute Error (MAE), Accuracy, Kappa statistic, Sensitivity and R-squared ($R^2$). The models are then evaluated on a case study building. The ground floor plan and detail information about the case study building have been presented in our previous work (Akanbi et al., 2019; Akinade et al., 2015).

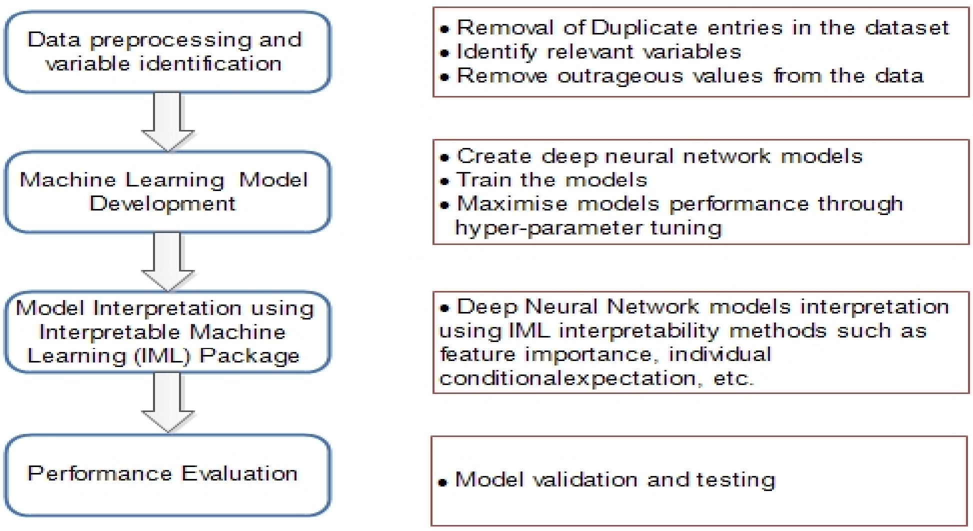


Figure 3: Research methodology outline

## 4.1 Data acquisition, pre-processing and variable selection

The data used in this work is made up of the building demolition records obtained from members of the UK's National Federation of Demolition Contractors (NFDC) and Institute of Demolition Engineers (IDE). Our informants are major players in the demolition industry in the UK. It should be mentioned at this juncture that, it is not always possible for the demolition engineers to get adequate records of materials from building demolition exercise. This is mostly due to lack of space, time and facility to segregate demolition rubbles on site. The practice is to transport the rubbles to the nearest Waste Transfer Stations (WTS) where proper segregation is done and the materials put into the correct route (reuse, recycle or landfill). The WTS would have been the ideal source of data for this work, but there is a major challenge of mapping outputs from waste segregation process to the actual buildings that produced the waste. This is because building rubbles from different demolition site are aggregated at the WTS before further processing.

Demolition records from 2,280 buildings were obtained. The dataset comprises information about buildings and the amount of different building materials obtained from the demolition work. Generally, Demolition Engineers keep as much information as possible about the building to be demolished. This building information includes the location of the building, owner of the building, building features such as gross floor area, volume, presence of mezzanine, down below, underground tank etc. With the support of our informants, five key features of buildings are identified as major determinants of the quantity of building materials recoverable from demolition work. These features include gross floor area (GFA), volume, number of floors, building architype and usage. The dataset also contains entries for each of the waste categories (reusable, recyclable and landfill). A negligible fraction (9 records, i.e. 0.004%) of the dataset contains missing information (i.e. the volume of the building). The missing volumes were calculated by multiplying the gross floor area of the building by the typical height of a building (i.e. 2.80m). Part of the dataset is presented in table 3 due to limited available space. The distribution of the dataset with respect to building architypes and building usage are presented in figures 4 and 5.

Table 3: Sample Building Demolition Data

| | | Building Features | | | | Output (tons) | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Id** | **Architype** | **Usage** | **GFA** | **Volume** | **Floors** | **Total** | **Recycle** | **Reuse** | **Dispose** |
| Bld_1 | Concrete | Offices | 1233.00 | 04315.50 | 5 | 0827.2192 | 0737.4018 | 0081.9335 | 0007.8838 |
| Bld_2 | Concrete | Offices | 4320.00 | 15121.00 | 3 | 0495.2443 | 0444.4498 | 0049.3833 | 0001.4111 |
| Bld_3 | Concrete | Offices | 3642.00 | 12782.00 | 6 | 2640.0006 | 2337.1200 | 0259.6800 | 0043.2006 |
| Bld_4 | Concrete | Education | 4582.00 | 16037.00 | 2 | 1382.0142 | 1105.6679 | 0122.8520 | 0153.4943 |
| Bld_5 | Concrete | Education | 3679.00 | 12876.50 | 2 | 1108.5596 | 0886.9059 | 0098.5451 | 0123.1086 |
| Bld_6 | Concrete | Education | 1553.00 | 05435.50 | 2 | 0469.0567 | 0375.3015 | 0041.7002 | 0052.0550 |
| Bld_7 | Concrete | Education | 1833.00 | 06415.50 | 2 | 0554.0118 | 0443.2702 | 0049.2522 | 0061.4893 |
| Bld_8 | Concrete | Education | 0014.00 | 00042.00 | 1 | 0012.0659 | 0009.6640 | 0001.0738 | 0001.3280 |
| Bld_9 | Concrete | Education | 0015.80 | 00047.50 | 1 | 0014.3046 | 0011.4497 | 0001.2722 | 0001.5827 |
| Bld_10 | Concrete | Education | 0015.10 | 00045.50 | 1 | 0012.8742 | 0010.3130 | 0001.1459 | 0001.4153 |
| Bld_11 | Concrete | Retail | 0272.00 | 01632.00 | 1 | 0161.7586 | 0143.3397 | 0015.9266 | 0002.4922 |
| Bld_12 | Concrete | Offices | 9526.00 | 33341.00 | 5 | 0196.5606 | 0175.9320 | 0019.5480 | 0001.0806 |
| Bld_13 | Concrete | Retail | 0957.50 | 76380.00 | 1 | 0498.1691 | 0383.2304 | 0042.5812 | 0072.3576 |
| Bld_14 | Concrete | Education | 0207.50 | 00726.00 | 1 | 0034.4868 | 0022.8271 | 0002.5363 | 0009.1234 |
| Bld_15 | Concrete | Education | 1069.00 | 03742.00 | 1 | 0126.5902 | 0108.6538 | 0012.0726 | 0005.8638 |

Unit of variables: GFA – $m^2$, Volume – $m^3$, Architype – number, Usage – number, Floors – number

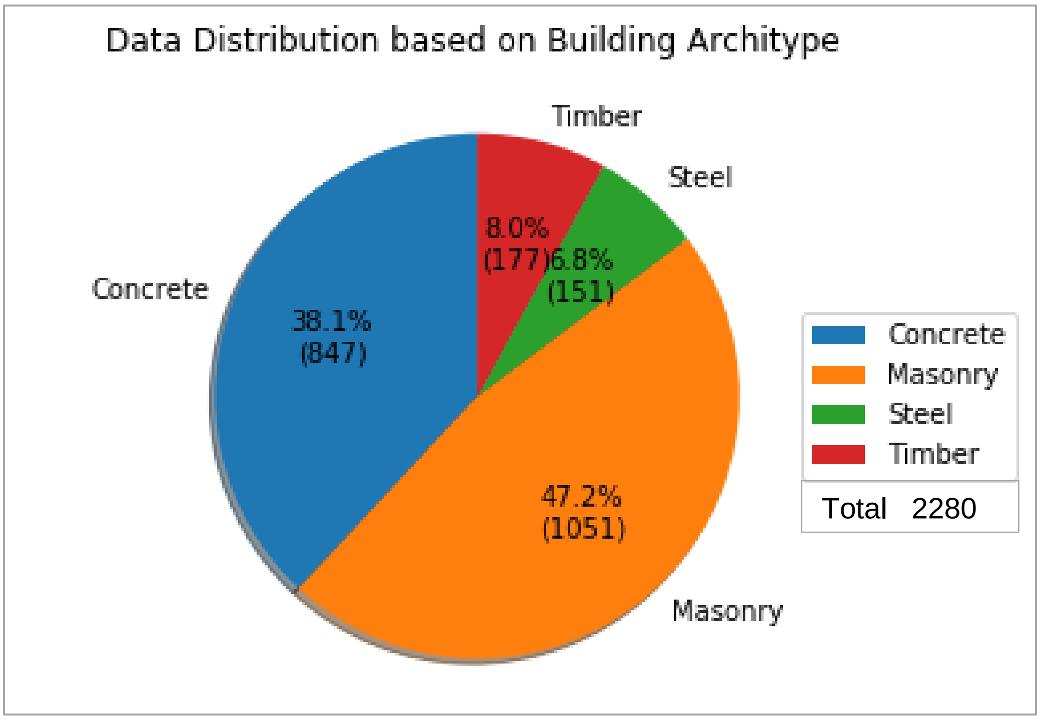


Figure 4: Distribution of Building Demolition Data based on Building Architype

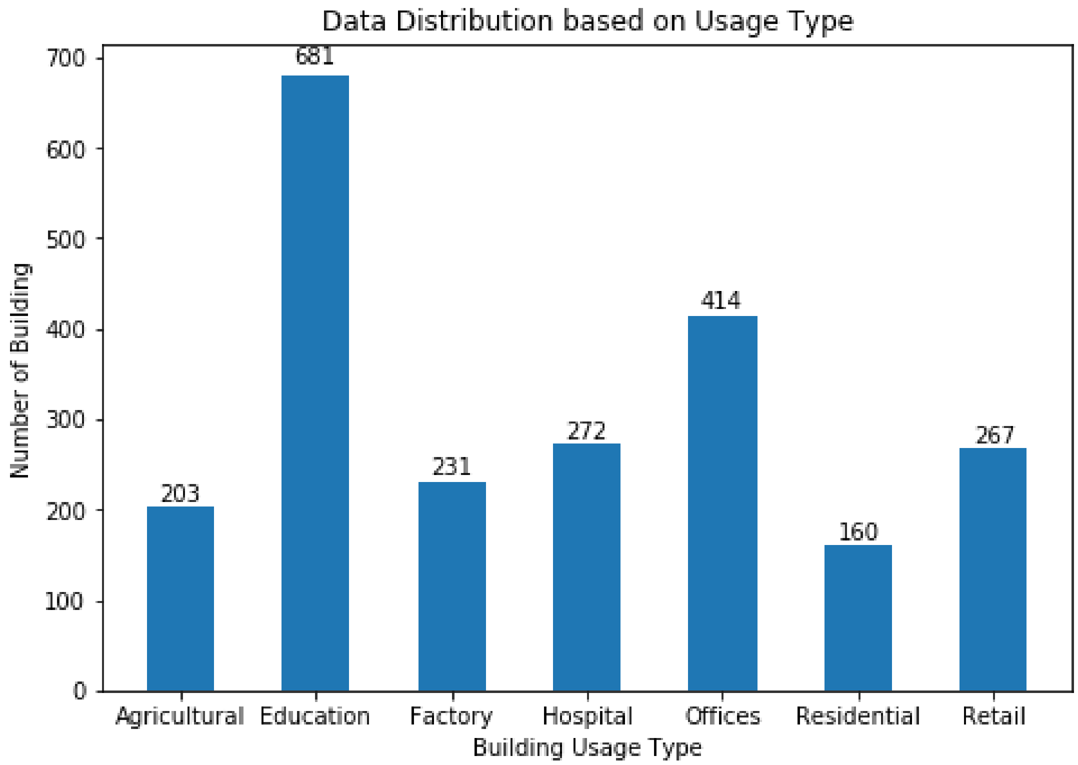


Figure 5: Distribution of Building Demolition Data based on Building Usage

## 4.2 Deep Neural Network Model Development

The architecture of DNN models for predicting the amount of building materials in tons based on the selected input is presented in this section. Three DNN models are developed to predict the amount of recycled, reused and landfill materials. Figure 6 shows the DNN architecture employed for the prediction of demolition waste and their categories. The dataset, after pre-processing was split into 80% for training, 10% for testing and 10% for validation. Precisely, 1708 observations were used to build the models through supervised training with the remaining 520 observations used for validation and testing of the models. Three regression models were developed in using the h2o deep learning framework in R data analysis and programming environment. h2o is an open source CRAN package, high-speed, and Java machine learning library software, designed with distributed algorithms scale to big data (Kochura et al., 2018). h2o has an interface to Python, Scala, R, Spark, and Hadoop.

Examining the sensitivity of deep neural networks is a way to find an optimal structure of the network (Al-Rahhal *et al*., 2016). To obtain the best validation results for the DNN models, there is need to determine the best structure of the neural network (i.e. the number of hidden layers, the number of activation units in each layer and activation functions) and control hyper-parameters. The control hyper-parameter was obtained through the use of random search. The random search approach is many times more efficient than the grid search method in that it replaces the regular grid by random sampling (Tixier et al., 2016). According to (Lee et al., 2011), the network architecture is responsible for classification and prediction accuracy improvement. The three DNN models are objectively evaluated with respect to architecture. The control parameters shown in table 4 are tuned to maximise each model's prediction accuracy on the test dataset. Different hyper-parameter combination obtained through random search are applied to each of the models. Optimal control settings are determined by a 5-fold cross-validation with 10% holdout.

In deep learning model development, the validation process prevents overfitting by comparing the performances of prediction algorithms created using the training data and selecting the algorithm that exhibits the best performance metric. In this case, an algorithm with the least Mean Absolute Error (MAE) is chosen as suggested in (Tixier et al., 2016). The accuracies of different DNN network structures for reusable materials, with respect to MAE and R-Squared, are depicted in figures 7 and 8. We settled for the optimal structure with four layers (6, 12, 12 and 6 neurons in layers 1, 2, 3 and 4), Rectifier activation function, $\ell 1 = 1e - 3$ , $\ell 2 = 1e - 8$, and epoch =250. This structure has the least MAE value of 17.9326 value and R-Squared value of 0.9818. Besides, we found out that for this specific regression problem the higher number of neurons were not making a significant difference in the accuracy of the model and which necessitate our choice of fewer neurons to reduce network's complexity. The optimal topology is denoted with a magenta line with small circles at the plotting points in figure 7 and 8. The architectures of the other two DNN models are determined accordingly, and appropriate optimal hyper-parameter values were obtained.

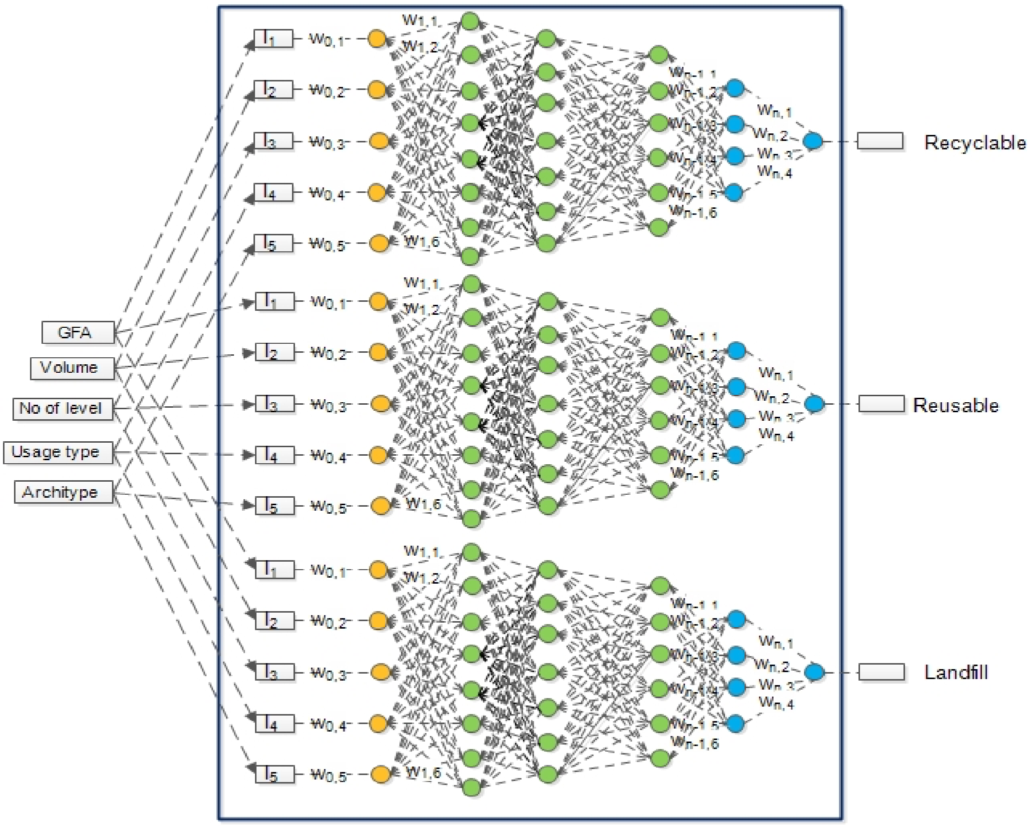


Figure 6: DNN Model Architecture for Demolition Waste Prediction

Table 4: Hyper-parameter combinations

| Parameter | List |
|---|---|
| Activation function | Rectifier, Maxout, RectifierWithDropout, Tanh, TanhWithDropout, etc. |
| layers | 1, 2, 3, 4 |
| neurons | 40, 100, 180, 270, 500 |
| rho | 0.9, 0.999 |
| epoch | 10, 30, 50, 100 |
| epsilon | 1e-10, 1e-4 |
| $\ell$1 regularisation | 0, 1e-4, 1e-7, 1e-8 |
| $\ell$2 regularisation | 0, 1e-4, 1e-6, 1e-7 |
| input_dropout_ratio | 0, 0.05 |

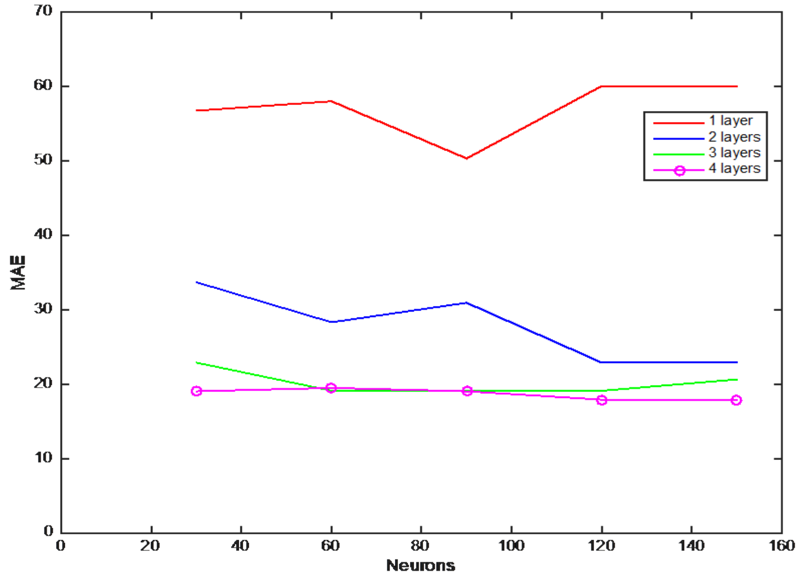


Figure 7: Accuracy of DNN configurations for reusability with MAE as the metric

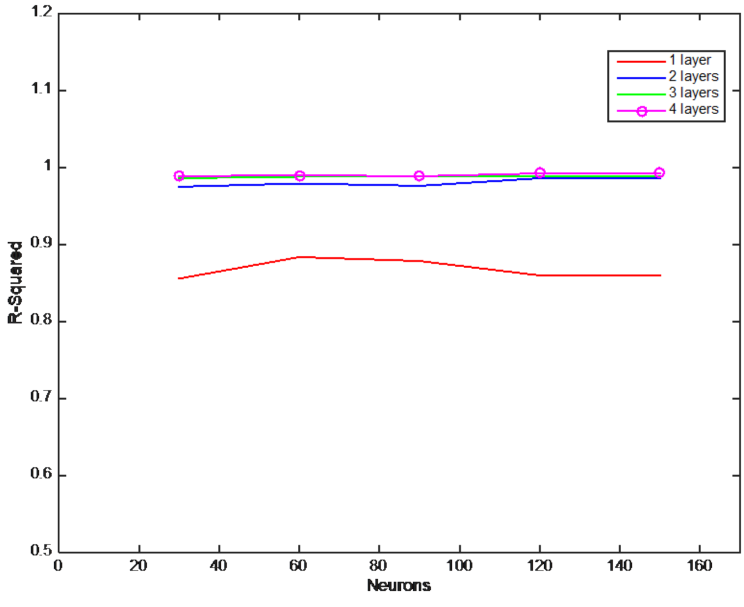


Figure 8: Accuracy of DNN configurations for reusability with R-Squared as the metric

There are several deep learning optimisation algorithms such as Least-squares methods (Gauss-Newton, Levenberg–Marquardt), quasi-Newton methods (Broyden–Fletcher–Goldfarb–Shanno (BFGS)) amongst others. These methods are too costly in terms of computation resources required for neural networks (Schmidhuber, 2015). Conjugate gradient (CG), Limited-memory-BFGS (L-BFGS) and other methods are fast alternatives, but the CG algorithm, in general, requires more cycles to reach the minimum and L-BFGS can overfit on a small training set (Bengio, 2012).

Stochastic Gradient Descent (SGD) algorithm is a fast training procedure for reducing the cost or loss function (computing a gradient overall training samples), compared with other optimisation techniques. (Bottou, 2010) The algorithm computes outputs, errors and the average gradient of observations, and adjusts the weights where necessary. Using a parallelisation technique with a suitable DNN architecture, the performance of the SGD algorithm over L-BFGS improves with the size of the training data (Bengio, 2012). The parallelised SGD (Recht et al., 2011) is applied in the development of the three DNN models. The parallelised SGD models a lock-free shared-memory system where each processor independently performs stochastic gradient updates. The lock-free stochastic gradient keeps a global result vector and allows each processor to update the vector without considering other processors. Under certain conditions, this asynchronous procedure preserves the convergence of stochastic gradient methods and results in ample speed-ups for many available cores (Recht et al., 2011). All models tuning, training and prediction were performed using the h2o framework in R. h2o was adopted because it is a fast and scalable open-source framework for machine learning applications development.

### 4.3 Effect of Small and Bias Data

According to Mayr et al. (2016), DNN is synonymous with big-data applications and, it results in overfitting when used on a small dataset. To mitigate the problem of overfitting, the dropout technique combined with SGD was incorporated in the training procedure. Data imbalance is a form of bias in machine learning, where the class distribution is not uniform among various classes. For instance, missing data also represent an aberration in data, which could significantly affect the prediction. The DNN structures used in this study (insensitive to imbalanced data) are similar to the classic DNN (Larochelle et al., 2009). The h2o framework automatically performs mean imputation for missing values during training.

### 4.4 Performance Metrics for Model Verification

The predictive accuracies of the three DNN models on test dataset were measured to assess their generalisation abilities as suggested by (LeCun et al., 2015). Mean Absolute Error (MAE) and R-squared were used to evaluate the performance of the DNN models. MAE and R-squared are scale-dependent metrics that provide reliable ways to quantify prediction error (Fan et al., 2017). The target is to minimise these metrics to obtain the highest prediction accuracy for the model. These metrics are defined in equations (8) and (9), where $t_i$ denotes target i, $y_i$ denotes prediction i and N is the number of testing observations.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|t_i - y_i| \qquad (8)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i - y_i)^2} \qquad (9)$$

The DNN models' complexity was determined by computing the time spent on training each model. The computational tool on which the simulation was carried out was a MacBook Pro (Intel Core i7 processor of 2.5 GHz and random-access memory of 16 GB), and the models were developed in the R language.

### 4.5 Model Testing and Evaluation

The accuracy of the three DNN models is tested with the use of R-Squared metrics. The use of R-Squared, as a performance metric for regression problems, shows the level of closeness of the predicted values to the actual values. The accuracies of the three DNN models, i.e. recyclable, reusable and landfill models, are presented in table 5. On the average, the DNN model for recyclable materials achieved 94.75% prediction accuracy, the DNN model for reusable materials achieved 97.89%, and the DNN model for landfill materials achieved 99.44% prediction accuracy. The overall average performance of the three models based on the R-squared performance metrics is 97.00%. This performance accuracy is in line with results obtained in similar construction related studies e.g. (Geyer and Singaravel, 2018; Singaravel et al., 2018). In Singaravel et al., (2018), deep learning based neural network models were used to predict the heating and cooling energy requirement of building designs. The R-squared values obtained ranged from 0.993 to 0.999. The component based neural network model developed in Geyer and Singaravel (2018) for building performance prediction achieved R-squared values that ranged from 0.848 to 0.999. A sample actual, predicted and absolute error values by the three DNN models are presented in tables 6 - 8. The three models' performance show an absolute error of less than 1.00 across all the testing dataset. The average absolute error from the evaluation results presented in figures 6 – 8 is 0.2116, an indication of a good generalisation capability of the three DNN models with no underfitting or overfitting of the training dataset.

Table 5: DNN Models Performance Accuracies

| **DNN model (Recyclable)** | | **DNN model (Reusable)** | | **DNN model (Landfill)** | |
|---|---|---|---|---|---|
| **Dataset** | **%accuracy (R2)** | **Dataset** | **%accuracy (R2)** | **Dataset** | **%accuracy (R2)** |
| training | 0.9508 | training | 0.9737 | training | 0.9935 |
| testing | 0.9616 | testing | 0.9818 | testing | 0.9947 |
| validation | 0.9302 | validation | 0.9812 | validation | 0.9949 |
| Average | **0.9475** | **Average** | **0.9789** | **Average** | **0.9944** |

Table 6: Actual and Predicted Values from Recyclable DNN Model - test data sample

| Actual | Prediction | Absolute error |
|---|---|---|
| 077.1742 | 077.2259 | 0.0517 |
| 114.8829 | 114.7919 | 0.0910 |
| 077.8434 | 077.7482 | 0.0952 |
| 011.4497 | 011.6348 | 0.1851 |
| 008.7131 | 008.9901 | 0.2770 |
| 077.1048 | 077.4129 | 0.3081 |
| 389.2500 | 389.7038 | 0.4538 |
| 378.0900 | 378.5168 | 0.4268 |
| 111.4478 | 111.8412 | 0.3934 |
| 389.2500 | 389.7038 | 0.4538 |

Table 7: Actual and Predicted Values from Reusable DNN Model based - test data sample

| Actual | Prediction | Absolute error |
|---|---|---|
| 22.1530 | 22.1276 | 0.0254 |
| 22.0569 | 22.1191 | 0.0622 |
| 22.2522 | 22.1458 | 0.1064 |
| 22.3512 | 22.1592 | 0.1920 |
| 21.8897 | 22.0844 | 0.1947 |
| 39.9520 | 39.7254 | 0.2266 |
| 21.8309 | 22.0581 | 0.2272 |
| 01.3981 | 01.1438 | 0.2543 |
| 10.3712 | 10.7135 | 0.3423 |
| 22.3141 | 22.0597 | 0.2544 |

Table 8: Actual and Predicted Values from Landfill DNN Model based - test data sample

| Actual | Prediction | Absolute error |
|---|---|---|
| 01.1043 | 01.1525 | 0.0482 |
| 12.6600 | 12.6110 | 0.0490 |
| 12.6600 | 12.6110 | 0.0490 |
| 68.3400 | 68.1930 | 0.1470 |
| 04.9700 | 04.7793 | 0.1907 |
| 01.0687 | 01.2613 | 0.1926 |
| 01.1683 | 00.9552 | 0.2131 |
| 01.0705 | 01.3510 | 0.2805 |
| 01.1813 | 00.8881 | 0.2932 |
| 00.1838 | 00.4474 | 0.2636 |

## 4.6 Model Evaluation with Case Study

Having evaluated the DNN models based on their accuracy measured with R-squared and mean absolute error. Next, we evaluate the models on the real-life use case. The DNN models were evaluated with a use case building while considering four scenarios of the structural components of the building. The four scenarios are: (i) concrete, (ii) steel, (iii) masonry, and (iv) timber. Table 9 shows the features of the case study building. The gross floor area of the building was derived from the summation of the floor areas of the three floors in the building while the volume of the building was calculated by multiplying the gross floor area with the height of the building.

Table 9: Design Features of the Case Study Building

| Feature | Value |
|---|---|
| Building usage type | Education - Office |
| Number of floors | 0003.00 |
| Area of the ground floor | 0492.00m$^2$ |
| Area of the 1st floor | 0351.00m$^2$ |
| Area of the 2nd floor | 0351.00m$^2$ |
| Height of the floor to ceiling (h) | 0002.80m |
| Gross floor area (gfa) | 1194.00m$^2$ |
| Volume of the building (gfa x h) | 3343.20m$^3$ |

Table 10 shows the results of the evaluation of the DNN models on the case study building. Four combinations of the building features are used for the evaluation to realise four possible architypes that a building could have. In table 11, the analysis of the predicted end-of-life arisings are presented. The analysis shows that the building with concrete has 73.61% recyclable, 11.31% reusable (direct reuse) and 15.08% dispose to landfill materials. While, the building with masonry has 56.98% recyclable, 39.44% reusable and 3.58% landfill materials. The building with steel generates 33.33%, 65.71, and 0.96% of recyclable, reusable and landfill materials. The building with timber frame produces recyclable, reusable and landfill arisings in the ratio of 16.12%, 83.37%, and 0.51%.  From the results, the building with timber frame generates the highest reusable end-of-life arisings followed by the building with steel frame. The building with the concrete frame generates the least reusable arisings followed by the building with the masonry frame. Similarly, the timber frame building generates the least waste to landfill followed by steel frame building.

Table 10: Result of Evaluation of the DNN Models with Case Study

| **Building Features** | | | | | **Predicted Outputs Values (tons)** | | | |
|---|---|---|---|---|---|---|---|---|
| **Architype** | **Usage** | **GFA** | **Volume** | **Floors** | **Recyclable** | **Reusable** | **Landfill** | **Total** |
| Concrete | Education | 1194.00m$^2$ | 3343.20m$^3$ | 0003 | 0595.68 | 0091.56 | 0122.02 | 0809.26 |
| Masonry | Education | 1194.00m$^2$ | 3343.20m$^3$ | 0003 | 0653.20 | 0452.18 | 0041.00 | 1146.39 |
| Steel | Education | 1194.00m$^2$ | 3343.20m$^3$ | 0003 | 0955.58 | 1884.32 | 0027.39 | 2867.29 |
| Timber | Education | 1194.00m$^2$ | 3343.20m$^3$ | 0003 | 0223.35 | 1155.27 | 0007.10 | 1385.72 |

Table 11: Analysis of the predicted end-of-life arisings

| **Architype** | **Recyclable** | **Reusable** | **Landfill** |
|---|---|---|---|
| Concrete | 73.61% | 11.31% | 15.08% |
| Masonry | 56.98% | 39.44% | 03.58% |
| Steel | 33.33% | 65.71% | 00.96% |
| Timber | 16.12% | 83.37% | 00.51% |

The distribution of the end-of-life arisings and their use cases as shown from the evaluation of the DNN models are consistent with results in previous studies (Akanbi et al., 2018; Akinade et al., 2015). Noticeably, there are slight variations in the distribution of the arisings for the different frame types when compare with the previous studies. For example, in Akanbi et al., (2018), timber frame building generates arisings in the ratio of 0.65 of reusable and 0.35 of recyclable whereas in the present study, the ratio is 0.83 reusable and 0.16 recyclable. The increase in the amount of reusable timber is due to factors such as the existence of the need for timber materials, enough time to carry out onsite sorting etc. at the time of demolition.

## 5 Discussion

The deep learning models developed in this work take advantage of the advancement in big data and machine learning algorithms to establish a meaningful relationship between the independent variables, (i.e. building architypes, building usage, building's gross floor area, number of floors and volume) and corresponding dependent variables (recyclable materials, reusable materials and landfill materials). The three DNN models developed have an average accuracy of 97% when R-squared is used as the performance metric. The independent variables contribute to the three DNN models' performance differently, for the recyclability DNN model, building usage type has the highest level of importance i.e.1.00 followed by gross floor area (0.95), number of floor (0.91), architype (0.76) and lastly volume (0.62) as shown in figure 9. In the reusability DNN model, the number of floors in a building is a major determinant with 1.00 level of importance, the least important variable is the volume with 0.64 level of importance. Figure 10 shows the variable importance levels of the independent variables for the reusability DNN model. In figure 11, the variable importance levels of the independent variables for the landfill DNN model is presented. The number of floors in a building has the highest level of importance (1.00), followed by the gross floor area with 0.87 level of importance. The least variable that contributes to the model is the volume with 0.23 level of importance.

The analysis of the variable importance shows that out of the five independent variables, the number of floors has the highest level of importance across the three models while the volume has the least level of importance across the three models. The architype (frame type) is the next least important consistently across the three models. The volume and architype consistently contribute less to the performance of the models, their level of importance across the three model ranges from 0.23 to 0.77 which justify their inclusion in the variables that determine the output of a demolition. Our choice of the building features used for training the DNN models was guided by the experts (i.e. demolition engineers, and refurbishment & demolition surveyor), the level of significance of these variables to the models' high performance justify their choice.

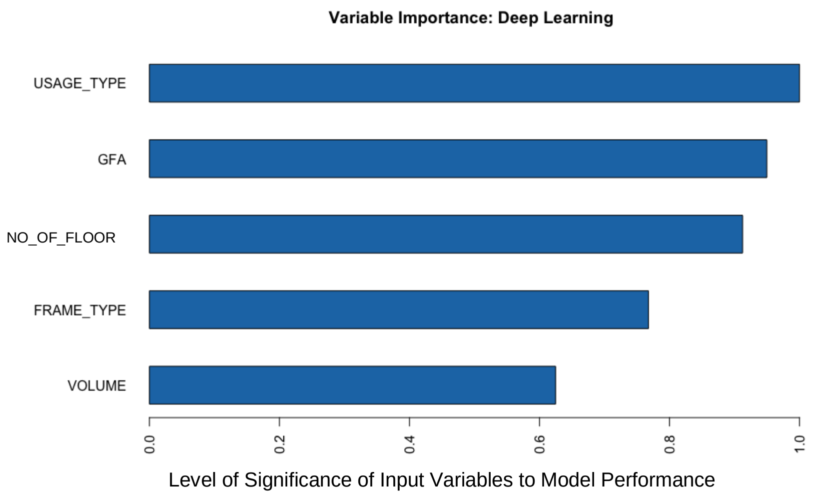


Figure 9: Variable Importance Plot for Recyclable DNN Model

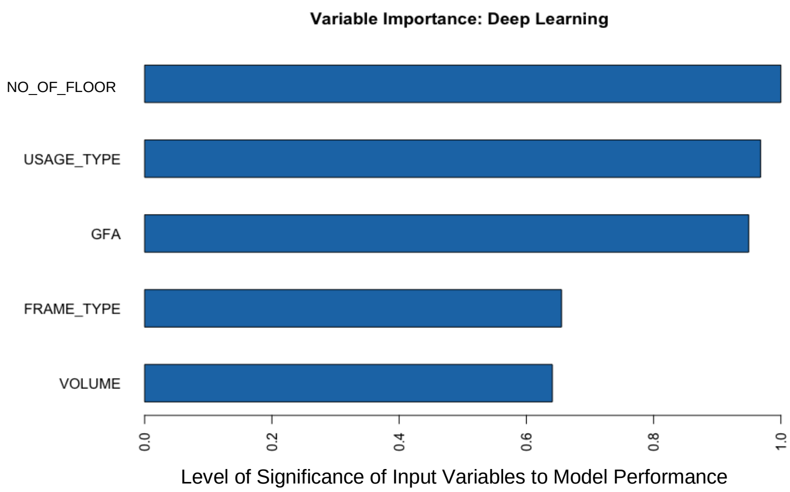


Figure 10: Variable Importance Plot for Reusable DNN Model

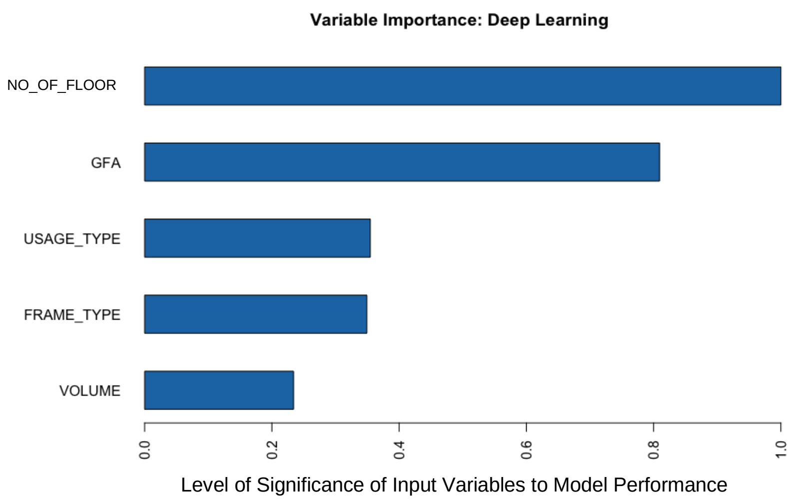


Figure 11: Variable Importance Plot for Landfill DNN Model

The results from the evaluation of the DNN models with different scenarios of the case study building confirm the conclusion of previous studies (Akanbi et al., 2019, 2018; Akinade et al., 2015) that timber and steel based buildings produce end-of-life materials that are mostly reusable through either direct reuse or recycling. The present study also shows the end-of-life performance of the masonry-based building. The masonry-based building generates end-of-life arising that is 56.98% recyclable, 39.44% reusable and 3.58% waste materials to landfill. The masonry-based building performs more than three times better than concrete-based building in terms of materials reusability. The reason for the masonry performance is not farfetched, bricks and blocks which are the basic components of a masonry building come in standard sizes, which makes them readily usable in other projects without any modification.

While the current results are in line with results from previous studies, the present study establishes the possibility of using basic information about building to predict the end-of-life arisings. Previous works depend on the availability of a well-defined federated building BIM of the building to estimate the end-of-life arisings. The prediction functionality provided by the DNN models in this study is particularly useful in the situation where there little or no information about a building that is meant to be deconstructed/demolished. This is the situation with the most buildings that are due to be demolished in the UK. When integrated with our BIM based system for evaluating the end-of-life performance of building design (Akanbi et al., 2019), the present work will provide the Pre-Deconstruction Analytics functionality. This functionality is required to provide the whole-life building performance analytics to support decision making at various point in the life cycle of building from design to deconstruction.

Considering the theories of AI and the tragedy of the commons that underpinned this study, the results have demonstrated the possibility of leveraging recent development in the field of machine learning (i.e. deep learning) which is a subfield of AI to facilitate responsible use of the limited common resources. The common resources in this case include the natural environment where virgin materials are extracted, building materials and landfill sites. Using an AI technique, the study provides a decision support tool to facilitate the end-of-life management of materials. Some of the decisions that require timely access to information about the building materials include adequate planning for skips to convey the materials, identification of supply chain for expected materials prior to actual demolition and timely identification of the storage requirements for safekeeping of the material for a later use.

## 6 Conclusion

Ensuring an effective circular economy in the construction industry requires the ability to accurately estimate the amount (in tons) of materials and wastes from deconstruction and demolition work. Determining the actual amount of materials from demolition and deconstruction work will facilitate adequate planning for materials reuse. Current strategies for estimating end-of-life arisings are largely manual and time consuming, which mostly lead to an increase in the eventual cost of disposal. Demolition data containing information about the features of buildings and various materials outputs in tons were used to develop deep neural networks for predicting building materials outputs based on selected building features. Using R-squared as a performance metric, the deep learning models developed achieved an overall average accuracy of 0.97 on all the dataset. The model for recyclable materials achieved 0.95 accuracy, while the model for reusable materials achieved 0.98 accuracy, and the model for landfill materials achieved 0.99 accuracy. The study shows that the number of floors in buildings contributes most to the performance levels achieved by the three models while the volume of the building contributes less to the performance.

This study has implications for both academic and practice. The academic implication of this study brought to the bare the application of machine learning algorithms for estimating the amount of recyclable, reusable and waste materials obtainable from buildings when demolished. The implication of this study for practice in the C&D industry is its provision of decision support functionality to demolition engineers, refurbishment & demolition surveyor and planners at the end-of-life of building prior to eventual demolition. Being able to easily and timely estimate the amount of materials that would arise from building demolition will lead to efficient planning for equipment and manpower requirements for the actual demolition process. It will also enable construction organisations' pursuit of materials circularity in their delivery of construction projects thereby contributing to the UK circular economy agenda.

Further work will be required to integrate the deep learning models developed into the existing BIM software such as Revit, AutoCAD, Bentley etc. where the required building feature for predicting end-of-life materials will be captured automatically from the BIM model to eliminate manual data entry which is usually prone to errors. The integration of the deep learning models with BIM software will increase the usability of the models among the construction industry stakeholders. Other features of the building such as the number of rooms, building elements, building components etc. will be considered in the future refinement of the models.

The limitation of the present work is that the deep learning models developed are based on data from the UK's Institute of Demolition Engineer and NFDC. The dataset contains information about the UK building stock only. Efforts will be made in the future to obtain building demolition data from the other part of the world to improve the robustness of the models.


# 7 Acknowledgement

The authors would like to acknowledge and express their sincere gratitude to the Engineering and Physical Sciences Research Council (EPSRC) and Innovate UK (Grant Reference No.

EP/N509012/1; Grant Application No. 54832–413479/File No. 102473) for providing the financial support for this study.

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